Evaluating the Economic Outcomes of the Abolition of Bihar's APMC Act in 2006

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Abstract

The state of Bihar abolished the Agricultural Produce Market Committee (APMC) Act in 2006, and became the first state in India to open its agricultural markets to private corporations and contract farming. Proponents of this policy change claim that this led to economic growth in Bihar and increased farmers' incomes, while critics argue that it left small and marginal farmers without protection and a secure livelihood. Our goal in this paper is to study the economic impacts of this policy, particularly on economic growth (as measured by night lights) and labor market outcomes. We also evaluate heterogeneity in treatment across Bihar. We are unable to find evidence that the policy led to economic growth, but find strong evidence that it failed to generate employment.

1 Introduction

In September 2020, the Parliament of India passed three bills which significantly reformed the organization of the agricultural sector by removing some key restrictions on the trade of agricultural produce in India. Prior to the passage of these bills, farmers in most states of the country were constrained to selling their produce in government-run markets – called Agricultural Market Produce Committees (APMCs) in their localities. They were not allowed to sell in markets in different parts of the country or to independently contract with private buyers. These restrictions were significantly eased by two of the 2020 reforms – the *Farmers' Produce Trade and Commerce Act* and the *Farmers' Agreement on Price Assurance and Farm Services Act* – which allowed farmers to access APMCs all over the country, as well as independently deal with private corporations and buyers. In effect, these bills ended the monopsony of APMCs.

These reforms were extremely controversial and led to nationwide protests by opponents, including farmer unions across the country. In fact, subject of APMCs has been controversial in India for decades, and several committees have been set up by different governments to look into their usefulness and validity. Critics of APMCs point out that since farmers are forced to go through government-appointed middlemen, these middlemen are able to cartelize and purchase agricultural produce at below-competitive prices. They add that leaving the private sector out of agriculture keeps away huge potential investment in agricultural infrastructure which it could have undertaken. They argue, therefore, that giving farmers access to competitive markets can increase incomes, promote investment, and lead to greater economic growth. Critics of the 2020 reforms, on the other hand, argue that APMCs protect small and marginal farmers – 82% of the agricultural workforce – by giving them a forum for price discovery and negotiation regardless of the quantity of produce they are able to bring to market. According to this argument, allowing the private sector to directly deal with small and marginal farmers would set the stage for these farmers to be exploited by large corporations, since they will be subject to less government oversight. These critics also suggest that only group of farmers which would benefit from these reforms is big farmers who are well-connected to private players.

In an unprecedented move at the time, the North Indian state of Bihar became the first Indian state to abolish its APMCs in 2006, 14 years before the recent reforms. In particular, the state of Bihar repealed the APMC Act, which gave legal backing to APMCs and their powers. In doing this, the state government set up agricultural cooperatives and allowed farmers to directly deal with private buyers. From a researcher's perspective, Bihar's repeal of the APMC act in 2006 is a natural experiment which can help us understand the potential effect the 2020 reforms will have on economic outcomes. It should be noted that the two policies are not exactly the same – Bihar abolished APMCs altogether while the 2020 reforms do not – but they are similar in that they give farmers the ability to sell their produce outside the government system. Therefore, a precise understanding of the economic effects of Bihar's policy change can help guide discourse on the recent reforms.

To our knowledge, the causal impact of Bihar's 2006 APMC Act revocation on economic outcomes has not yet been studied. In this paper, we employ a difference-in-differences design to accomplish this goal. We are specifically interested in the impact of Bihar's policy change on economic growth and labor market outcomes. We use night lights – a satellite measure of nighttime luminosity – as a proxy for economic growth. With respect to labor market, we look at employment rates, the distribution of the labor force across sectors, as well as investment in education (as measured by literacy rate).

Our second contribution is a rich analysis of treatment heterogeneity, which is facilitated by our large dataset (see next section). In addition to looking at the overall effect of Bihar's policy change, it is also important to look at which subgroups of the population experienced these effects more (least) strongly, since much of the debate over the recent reforms is on who exactly they benefit. To estimate heterogeneity across various groups, we employ a third-differences (or difference-in-differences-in-differences) design, which is described in the next section.

Overall, we do not find strong evidence that Bihar's policy change led to an increase in night lights. We do, however, find heterogeneity in the effect of the policy change on night lights within Bihar. In addition, we find strong evidence that the policy change failed to generate non-agricultural employment in the state – but in fact led to a minor decline in non-agricultural employment. To arrive at these findings, we organize the paper as follows. In section 2, we describe our data. In section 3, we lay out our empirical strategy in greater detail. In section 4, we present and discuss our empirical results. Finally, in section 5, we offer a concluding discussion.

2 Data

Our primary data on economic and labor market outcomes for the states, districts and subdistricts of India comes from the SHRUG platform (The Socioeconomic High-resolution Rural-Urban Geographic Platform for India). The SHRUG is an open data platform describing multidimensional socioeconomic development across 600,000 villages and towns in India. We use data on labor market outcomes (employment rate and literacy rate) from the economic and population censuses from this platform. We also use data on nighttime lights from this platform, which is a highly significant proxy for population, employment, per-capita consumption, and electrification at very local levels, as in Asher (2021).

The first dataset we used in our SHRUG's night lights dataset, which has data on gridded night lights across India, matched to village and town polygons, for all years ranging from 1994-2013. The quantity of data across many years, as well as the depth of the data at the microlevel, makes this dataset an extremely rich dataset, thus imperative to our analysis. As mentioned above, night lights are widely used as a proxy for electrification or economic activity, where time series data on economic activity is otherwise not available. To prepare this dataset for our analysis, we used the "mean light" variable which is essentially the total light of the area divided by the number of cells, in order to not let differences in size of the area measured influence our results. More specifically, we used the $\log(1+x)$ transformation for all the outcome variables in our analyses, to be able to get proportional estimates and avoid the problem of taking the logarithm of 0. Since $\log(1+x)$ and $\log x$ are similar when x is not very small, we found this transformation to be useful. Furthermore, we removed observations from the required columns where the data was missing or NA, as there was only a small percentage of such observations. We then merged this dataset with the economic census data available through the SHRUG platform itself, in order to include relevant controls in our analysis.

The controls we included were total population size and area of the village in hectares, in order to control for larger villages; tar road - an indicator variable that represents the accessibility of the village by a paved road and can be used as proxy for development; and proportions of Scheduled Castes (SC) and Scheduled Tribes (ST) in the population - tribal and so-called "lower-caste" communities which are very relevant in policy and politics in Bihar.

The next dataset we explored is the Indian government's Economic Census dataset that provided us with information on the total (non farm) employment, manufacturing employment, and services employment for the years 1990, 1998, 2005, 2013. As seen in Table 1, Figure 2 and 3, the low manufacturing and service employment rates, indicate that the states in our analysis were highly involved in the agricultural sector, thus making them relevant to our study. To prepare this dataset for our analysis, we first calculated the employment rate, as a percentage of the total population, in order to control for differences in population sizes of the various villages studied. Similar to the nightlights dataset, we then used the $\log(1 + x)$ transformation of employment rate.

The last dataset involved in our study is the government's population census, obtained from the SHRUG platform described above. From this dataset, we obtained the literacy information for the years 1991, 2001 and 2011, used in our analysis. Once again, we calculated literacy rate as a percentage of total population, and took the $\log(1 + x)$ transformation of literacy rate as our independent variable in our analysis. Section 4 elaborates in more detail the reason behind our choice of outcome variables. Figures 1-4 confirm the parallel trend assumption of our pre-trends, discussed below.

3 Empirical Strategy

In order to estimate the causal impact of Bihar's revocation of the APMC act, we use a difference-in-differences design. Our control group includes a total of 10 states: Uttar Pradesh, Jharkhand, Chhattisgarh, Uttarakhand, Madhya Pradesh, Haryana, Punjab, Rajasthan, Gujarat, and Maharashtra. These are all primarily agricultural states located in North and Central India, and had the APMC act in force in all years of our sample.

We estimate regressions of the form

$$\ln(1 + Y_{ist}) = \gamma_s + \eta_t + \beta D_{it} + \delta' \mathbf{W}_{it} + \varepsilon_{ist} \tag{1}$$

where i denotes village, s denotes states, and t denotes year. γ_s and η_t denote state and year fixed effects, respectively. Y_{ist} is the outcome variable for village i in state s in year t, D_{st} is an indicator for whether state s is treated in year t, so $D_{st} = 1$ only when s is Bihar and $t \geq 2006$. $\mathbf{W}_{it}$ is a vector of village-level controls. We are primarily interested in β, the difference-in-difference estimate. Under the parallel trends assumption – that the year-by-year change of the outcome $\ln(1 + Y_{ist})$ would be the same in the treated and control groups for each year in the absence of the treatment – β identifies the Average Treatment Effect on the Treated (ATT): the average causal effect of the treatment on $\ln(1 + Y_{ist})$ for Bihar. If Y_{ist} is not very small, β can also understood to be the proportional increase (decrease) of nightlights caused by the treatment. To check the parallel trends assumption, we verify pre-trends in Bihar and control states for our outcome variables of interest – as shown in figures $1 - 4$.

As explained by Bertrand et al. (2004), standard errors in differences-in-differences designs can be highly misleading if they are not made robust to serial correlation. Since the treatment is given by state, we would also like our standard errors to account for within-state correlation in the error terms ε_{ist}. Therefore, in our regressions we cluster standard errors by state. This, however, leads to the common "few-clusters" problem and we effectively reduce our sample size to 11 (we have a total of 11 states in our analysis), which can lead to biased standard error estimates. A potential solution to this could be clustering at a lower level, such as the district level. Clustering by district entails the additional assumption that $\mathrm{Cov}(Y_{ist}, Y_{i's't'}) = 0$ for all values of i, i', s, s', t, t' as long as villages i and i' are in different districts. In some policy analyses, this might be a reasonable assumption since the district administration is most directly responsible for policy implementation. However, in our case the policy fundamentally changes the organization of the agricultural sector – which employs a vast majority of Bihar's workers – so there is little reason to expect error terms ε_{ist} to be uncorrelated across different districts of Bihar. Thus, we only consider standard errors clustered by state, even given the caveat that we have a small number of clusters.

A second concern with few clusters is that if there is only one treated state and a handful of control states, the difference-in-differences estimate might attribute the effect of other state-specific shocks that occurred around the same time to the policy change. While in our application it is reasonable to assume that this is not the case – considering how large the impact of revoking the APMC act would be in a state as heavily agricultural as Bihar compared to other shocks – we also estimate "triple-difference" models, which are robust to such state-specific shocks. This was the approach used by Garthwaite et al. (2014) in a study design similar to ours. In a triple-difference design, we estimate the heterogenous causal effect of a treatment on a particular subpopulation of the treated group (or heterogeneity based on a continuous variable). We use regressions of the form

$$\ln(1 + Y_{igst}) = (\gamma_s \times g) + (\eta_t \times g) + (\gamma_s \times \eta_t) + \beta(D_{st} \times g) + \varepsilon_{igst} \quad (2)$$

where g can be continuous or binary. Here, i is village, g is subgroup (or a realization of the continuous variable), s is state, and t is year g. β is the triple-difference estimator, which gives difference between the treatment effect on group g (or, if g is a continuous variable, of an observation which takes value g) and the treatment effect on others in Bihar. We also include all interactions between state, time, and g.

While triple-difference and difference-in-differences regressions are estimating different things (one estimates the average treated effect, one estimates heterogeneity in treatment effect), triple-difference regressions help us in two ways. First, due to the interaction $\gamma_s \times \eta_t$, it is robust to arbitrary shocks in the treated state which could bias difference-in-difference estimates. Second, it enables us to estimate treatment heterogeneity for various g – which is one of the main goals of this paper.

4 Results

As mentioned in the introduction, we are interested in two classes of outcomes. The first is night lights, which we use as a proxy for economic growth. The second is labor market outcomes – in particular, total non-farm (non-agricultural) employment rate, employment rate in the manufacturing sector, employment rate in the tertiary sector, and literacy rate. We use literacy rate in our analysis of labor market outcomes since it reflects labor market decisions – people might choose to get educated if they want to move into a line of work which requires education. Conversely, people might also choose not to get educated if they are exposed to more lucrative job opportunities since this increases the opportunity cost of education.

For each of the two classes of outcomes, we present difference-in-differences and triple-difference results. In our triple-differences, we study treatment heterogeneity over two broad classifications: by development indicators (whether the village has power for all residents and for agricultural use and whether the village is accessible by a tar – solid – road), and by socioeconomic village characteristics (population, village area, literacy rate, and proportion of the population which belongs scheduled castes/scheduled tribes). For night lights, we also look at treatment heterogeneity by non-farm employment.

4.1 Night Lights

We are interested in the outcome $\ln(1 + \mathrm{nl})$, where "nl" is the average luminosity of night lights measured across a village by a satellite. Table 2 reports difference-in-differences results for night lights. In column (2), we additionally include an interaction between employment rate and the treatment dummy to account for heterogeneity by employment rate. In both cases, we find no evidence that the 2006 policy change in Bihar causally affected night lights. We, however, also do not have evidence to claim that the policy had a null effect on night lights, since with a standard error of 0.07 (state-clustered) for a point estimate of < 0.060, we do not get a sharp 95% confidence about 0.[1] The point estimate is positive and indicates a 5.8% – 6.0% increase in night lights as a result of the policy, but we do not have enough clusters to be able to get sharp confidence intervals with robust standard errors. In future research, alternative methods can be explored to get sharper estimates.

We do, however, find interesting results in our analysis of treatment heterogeneity. These are reported in column (2) of table 2 and in table 3. Most notably, we

[1] A 95% normal confidence interval with these standard errors is approximately $(-0.08, 0.19)$, which is very wide on log scale.

see in both tables that villages with higher non-farm employment rates saw a smaller increase in night lights as a result of the policy as opposed to villages with lower non-farm employment. This is seen from the coefficient -0.053 on the interaction term in 2 and the coefficient -0.042 in Panel A of table 3.[2] In other words, while we cannot say whether the policy led to statewide economic growth, our results do support the conclusion that low non-farm employment villages saw more economic growth in response to the policy compared to high non-farm employment villages. This is intuitive, since villages with low non-farm employment disproportionately have high farm (agricultural) employment, and thus are more directly affected by the policy change. This is the closest we can get to claiming that the policy led to economic growth – that highly agricultural regions of the state grew in a relative sense.

Panel B of table 3 reports treatment heterogeneity over various development and socioeconomic variables. Most notably, we see that villages connected by a tar road saw more growth compared to villages without one, pointing to the fact that more developed villages reaped larger benefits. Villages with power for all residents saw less growth, but this seems to be a product of the fact that we use night lights to proxy for growth – villages that already completely electrified have less scope to see an increase in night lights than ones which are not completely electrified.

4.2 Labor Market Outcomes

The most significant finding of this paper is that Bihar's 2006 policy failed to generate non-farm employment – but, rather, seem to have caused a minor contraction in non-farm employment. Difference-in-difference estimates for labor market outcomes are shown in Table 4. In Columns (1) and (2), we see that the difference-in-difference estimates for the effect of the policy on total non-farm employment rate and employment rate in the services (tertiary) sector of the economy are negative, at a 95% confidence level (standard errors clustered by state). We do not find any evidence for a change in employment rate in the manufacturing sector, or in literacy rate.

Our finding is at odds with arguments made by critics of the APMC system. These critics suggest that liberalizing the agriculture sector will lead to overall economic growth and generate employment opportunities across sectors. Our results

[2] The similarity of these two coefficients also suggests robustness of this result.

suggest that the contraction in non-farm employment was driven by a decline in the services sector rather than in the manufacturing sector. The services sector – comprising a wide variety of service-based occupations ranging from plumbing to teaching – accounted for more than 50% of Bihar's state GDP in each of the years in consideration, but hired a far smaller percentage of the workforce than agriculture, which accounted for a far smaller percentage of the state GDP. Therefore, if there was employment growth driven by overall economic growth, we would expect to see a shift of workers from agriculture to the more lucrative services sector, which we do not see. An alternative explanation for the negative effect on employment rates in the non-farm sector might be that the agriculture in an APMC-free Bihar became so lucrative that workers from other sectors decided to move into agriculture. This, however, is highly unlikely based on the results we see. Table 4 suggests that the revocation of the APMC act led to approximately a 0.8% decrease in total employment rate and a 0.7% decrease in tertiary employment rate, effect sizes which are too small to explain such a strong shift in the labor market.

At the same time, it would also be wrong to suggest that our regression results conclusively show that the policy caused a significant decrease in non-farm employment, due to the small effect sizes. The safe conclusion from these small negative effects, therefore, is that the policy failed to generate employment. This could be due to the policy failing to generate any meaningful economic growth (see section 4.1) or due to the policy generating what is often called "jobless growth" (see section 5).

Table 5 shows triple difference estimates for treatment heterogeneity. Overall, the only significant heterogeneity we find seems to be based on whether or not a village has power for all residents, which saw more positive employment effects (columns (1) - (3)). The first two rows of column (4) indicate that more electrified villages saw smaller gains in literacy, which could perhaps be explained by a tighter job market in less electrified villages, which both incentivizes education to access better job opportunities, as well as reduces the opportunity cost of education. However, without further examination into literacy – which is beyond our scope – it is hard to concretely explain this heterogeneity in the effect on literacy rates.

5 Discussion

Our results paint a picture which is all-too-familiar in India – one of jobless growth. First of all, we find no evidence to support the claim that the revoking of Bihar's 2006 APMC Act generated economic growth in Bihar. Even if we are to accept suggestive facts (as we saw in the heterogeneity analysis in section 4.1) as evidence of *some* economic growth, our results in section 4.2 then point to economic growth without any real growth in employment. Therefore, in summary, our general conclusions in this paper are:

1. While we do not see evidence of economic growth as measured by night lights, we do see that highly agricultural regions of Bihar experienced more growth relative to less agricultural regions of Bihar.

2. The policy did not lead to non-farm employment growth – in fact, our estimates suggest a small contraction in non-farm employment.

3. Therefore, even if the policy led to some economic growth concentrated in a few regions of the state, its benefits did not spread across the state, since we would expect to see significant growth in state-wide employment if that was the case.

Future research can guide this discussion further. In particular, it would help to explore alternative methods to estimate the effect of the policy on night lights with greater certainty. If we find that the policy did indeed lead to growth, the question to ask then is why this growth was "jobless" and not complemented by employment. Potential avenues of exploration could be whether this growth was accompanied by infrastructural development.

References

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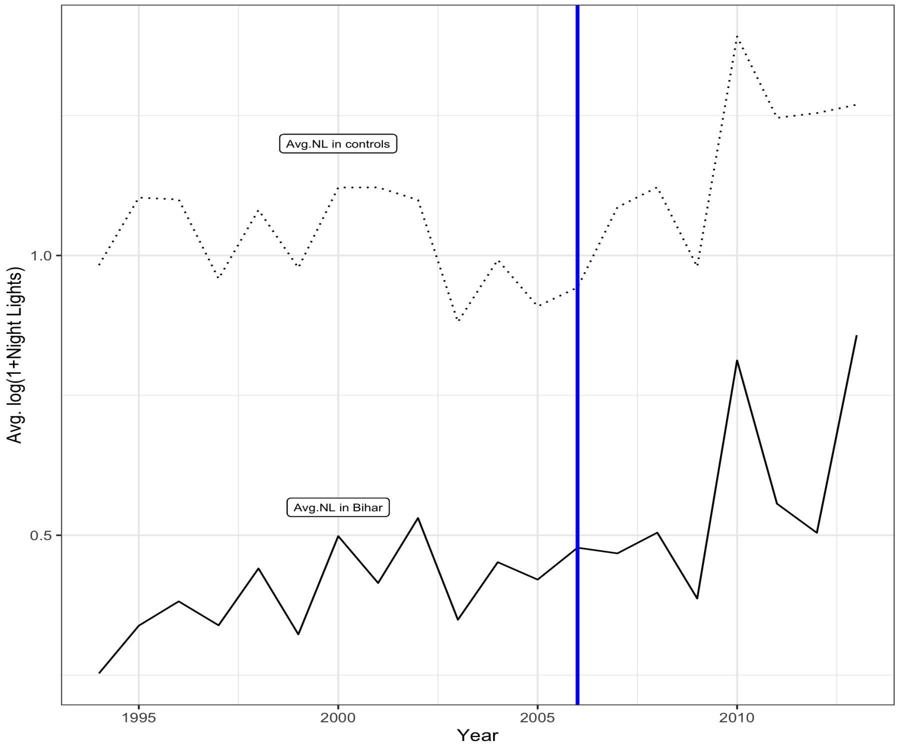
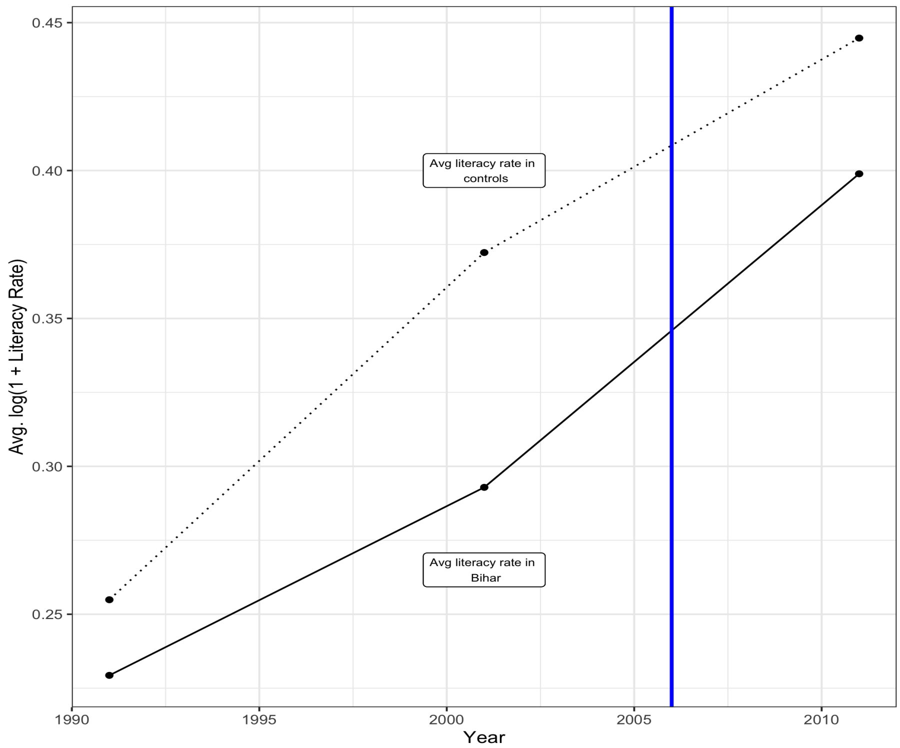
Appendix

Figure 1: Long term Night Lights trends in Bihar vs other states



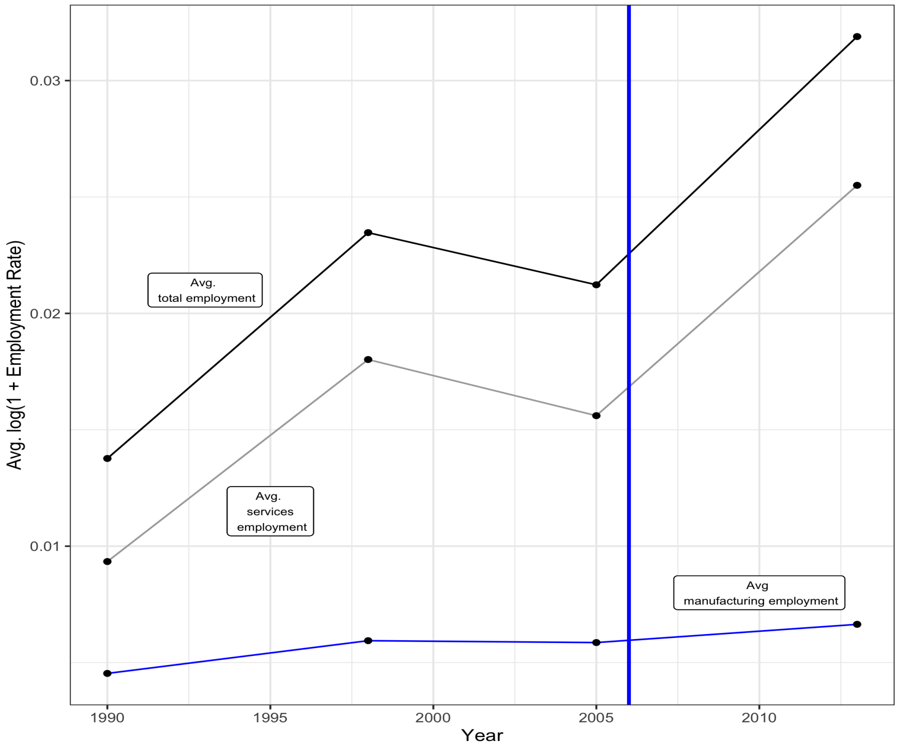
The figure above represents the trend of nighttime lights pre and post treatment, from 1994-2013. The y axis is the log(1+night lights) as explained in Section 2, and the x axis is the year. The solid line represents the treatment state Bihar, and the dotted line represents the average night lights of the control states. The vertical blue line represents the year of policy change studied, which is 2006.

Figure 2: Long term Literacy Rate trends in Bihar vs other states



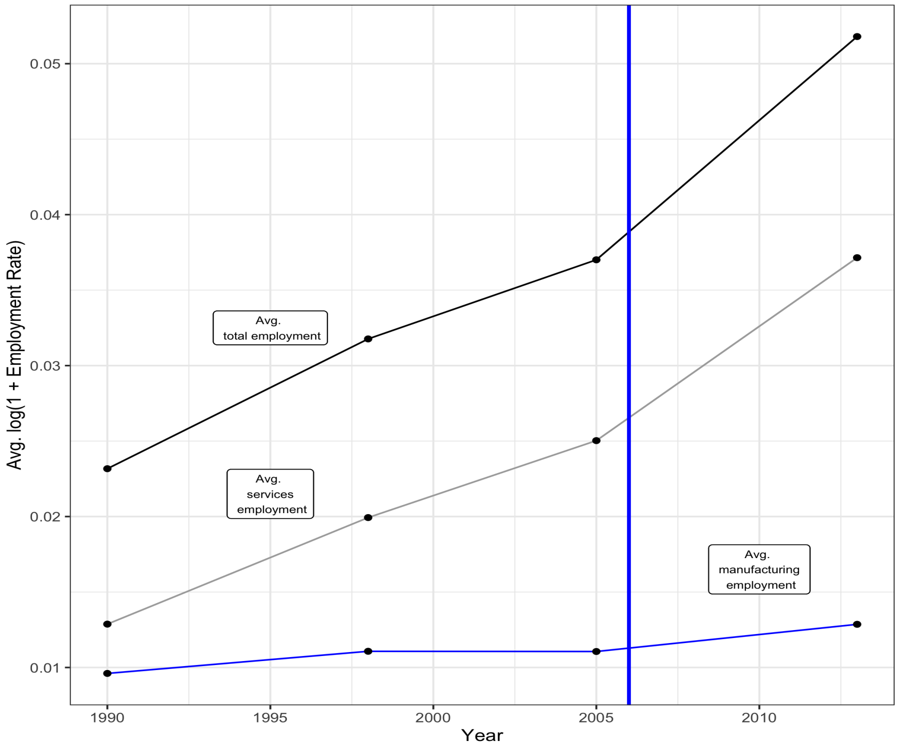
The graph above represents the trend of literacy rates pre and post treatment, from 1990-2013. The y axis is the log(1+literacy rate) as explained in Section 2, and the x axis is the year. The solid line represents the treatment state Bihar, and the dotted line represents the average night lights of the control states. The vertical blue line represents the year of policy change studied, which is 2006.

Figure 3: Long term Employment Rate trends in Bihar



The figure above represents employment rate trends pre and post treatment in Bihar only. The black line represents the average total (non-farm) employment rate, the dark grey line represents the average services employment rate, and the blue line represents the average manufacturing employment rate. The Y axis is the average of log(1+employment rate), for each of the respective employment types, and the X axis is the year. Similar to above, the vertical blue line represents the year of policy change studied, which is 2006.

Figure 4: Long term Employment Rate trends in the control states



The figure above represents employment rate trends pre and post treatment in all the control states. The black line represents the average total (non farm) employment across all the controls, the dark grey line represents the average services employment, and the blue line represents the average manufacturing employment. The Y axis is the average of log(1+employment), for each of the respective employment types, and the X axis is the year. Similar to above, the vertical blue line represents the year of policy change studied, which is 2006.

Table 1: Summary Statistics

Variable	Mean	Std Dev
Literacy Rate	0.456	0.176
Population	1335.264	13505.025
Scheduled Caste (SC) as a % of population	0.179	0.194
Scheduled Tribes (ST) as a % of population	0.143	0.294
Area	407.054	1655.13
Mean Night Lights	3.405	5.307
Total (non farm) employment rate	0.043	0.62
Manufacturing employment rate	0.0139	0.395
Services employment rate	0.027	0.41

Table 2: Difference-in-differences results for night lights

	(1)	(2)
	No interaction	Interaction
DID	0.058	0.060
	(0.070)	(0.070)
Employment rate × DID	.	-0.053**
		(0.016)
Population	0.000	0.000
	(0.000)	(0.000)
Area	0.000	0.000
	(0.000)	(0.000)
Tar road	0.351***	0.351***
	(0.025)	(0.025)
SC	0.000	0.000
	(0.000)	(0.000)
ST	0.000	0.000
	(0.000)	(0.000)
Literacy	0.000	0.000
	(0.000)	(0.000)
Employment Rate	0.051**	0.059**
	(0.014)	(0.016)
N	5918253	5918253

Standard errors in parentheses,, clustered by state

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Triple-difference estimates for treatment heterogeneity in night lights

	(1)
A. Employment	
Employment rate	-0.042*
	(0.022)
B. Development Indicators	
Power (all)	-0.220***
	(0.032)
Power (agriculture)	0.043***
	(0.000)
Tar road	0.036**
	(0.012)
C. Socioeconomic factors	
Population	0.000
	(0.000)
Area	0.000
	(0.000)
Proportion rural	0.001
	(0.014)
Proportion SC	-0.100
	(0.068)
Proportion ST	-0.106
	(0.094)
Literacy	0.002
	(0.116)

Standard errors in parentheses, clustered by state

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Difference-in-differences results for labor market outcomes

	(1) Total Emp.	(2) Services	(3) Manufacturing	(4) Literacy
DID	−0.008**	−0.007***	−0.001	0.009
	(0.002)	(0.001)	(0.001)	(0.011)
Population	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Area	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Tar Road	0.009***	0.007***	0.003**	0.027***
	(0.001)	(0.001)	(0.001)	(0.000)
SC	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
ST	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Literacy	0.000	0.000	0.000	
	(0.000)	(0.000)	(0.000)	
N	1258906	1258906	1258906	794434

Standard errors in parentheses,, clustered by state

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Triple-difference estimates for treatment heterogeneity in labor market outcomes

	(1) Total Emp.	(2) Services	(3) Manufacturing	(4) Literacy
	A. Development Indicators			
Power (all)	0.005***	0.002***	0.003***	-0.004***
	(0.002)	(0.001)	(0.001)	(0.001)
Power (agriculture)	0.003	0.0004	0.002***	-0.011***
	(0.000)	(0.000)	(0.000)	(0.001)
Tar road	0.001	0.000	0.002	0.002
	(0.002)	(0.001)	(0.001)	(0.002)
	B. Socioeconomic factors			
Population	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Area	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Proportion rural	0.001	0.095	0.003	0.032***
	(0.014)	(0.009)	(0.008)	(0.002)
Proportion SC	0.002	0.006**	0.001	0.135
	(0.006)	(0.002)	(0.003)	(0.010)
Proportion ST	0.008	0.009***	0.001	0.046***
	(0.006)	(0.002)	(0.002)	(0.009)

Standard errors in parentheses, clustered by state

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$